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Abstract

We exploit firm-level data on robot adoption and use an event-study approach to study the unexplored relationship between robotisation and innovation. Instead of an enabling effect, we find a negative association between robot adoption and the probability to introduce product innovations, as well as their number; the results emerge using different proxy of product innovation. However, large-scale investments in mechanisation cancel-out the negative effect and show a positive association with R&D expenditure. We rationalise and interpret the findings suggesting that a piecewise substitutive relationship exists between process and product innovation. Large investments relax the product-process trade-off, as substantial R&D investments to accrue absorptive capacity are mobilised; as a result, they make less binding the allocation dilemma between implementing robot technology and designing and trialling new products. Finally, we discuss whether industrial robots studied here and in the literature feature enabling capabilities at all. The study has important implications for our understanding of the role of robots for firms' operations and strategies, as well as for policy design.

Keywords: robots; automation; product innovation; absorptive capacity; Spain

JEL Codes: O31; O33;

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1. Introduction

Historically, mechanisation of production has always been accompanied by questions about its impact on the incentive to reallocate resources, with a natural focus on the substitutability of labour (Mokyr et al. 2015). However, labour substitution is only one of the effects of automation. In this paper, we study whether the adoption of robot technology influences the rate and direction of innovative activities.

In essence, robots are capital goods. However, contemporary robots are depicted as increasingly 'malleable', or flexible, capital goods – multi-purpose equipment capable of executing different tasks with little re-programming. Growing robot flexibility is a clear trend, as robot technology is augmented by other technologies characterising the fourth industrial revolution (Benassi et al. 2022; Martinelli et al. 2021), both hardware (e.g., sensors, or additive manufacturing technologies) and software (e.g., artificial intelligence algorithms). Robots become a component in larger systems, such as cyber-physical systems and advanced digital production technologies (UNIDO, 2019). As such, it is possible to hypothesise that robot adoption will induce changes in firms' behaviours that go beyond the well-known replacement and productivity effects on employment (Autor, 2019) and that are more 'enabling' in nature. This hypothesis begins to accumulate empirical support (Hirvonen et al. 2022). At the same time, current robots are "the most recent iteration of industrial automation technologies that have existed for a very long time" (Fernandez-Macias et al. 2021) that continue to operate in specific and constrained environments. Hence, their enabling capability might be limited if firms are not able (or do not plan) to exploit it. We shed some new light on this by measuring how product innovation and R&D expenditure changes when robots are adopted at the firm level.

Excluding robot vendors, for all other firms robots are process technology. Hence, robot adoption might be considered a form of process innovation. From this perspective, our analysis extends the reach of automation studies from the labour market perspective to a microeconomics of innovation one. Studying the interplay of robot adoption and innovation can provide insights on the more general relationship between process and product innovation – whether it is one of substitutability or synergy. At the root of process and product innovation there are different strategic considerations: process innovation is mainly driven by efficiency and cost cutting reasons; product innovation is mainly driven by the capture of value and market shares or creation(penetration) of(in) new markets (Utterback and Abernathy 1975; Klepper 1996; Damanpour and Gopalakrishnan 2001). While theoretical literature has modelled firms' portfolio choice between product and process innovation (Lambertini 2003), the empirical evidence is still scant – even more so for the case of robotisation. In summary, the paper contributes to the growing, yet nascent, strand of studies analysing firm-level data on robot adoption with a unique perspective on the nexus between the adoption of industrial robots and product innovation performance.

We exploit a unique dataset of Spanish firms, coming from the Survey on Firm Strategies (Encuesta Sobre Estrategias Empresariales, or ESEE) and implement an event-study approach (a generalised diff-in-diff model) to relate different indicators of product innovation to robotisation. We show that robot adoption is negatively associated to product innovation in the long term. We isolate the effect of large- vs small-scale investments mechanisation and find that the negative association with product innovation disappears for large-scale investments. Firms that are located in the top quartile of the investment distribution experience a positive increase in R&D expenditure (but not innovation), while firms in the bottom quartile display a negative relationship with both product innovation and R&D. We interpret the findings along a few lines of reasoning and converge on the idea that a conditional (on the scale of investment) substitutability exists between robotisation (process change) and the introduction of new products. In particular, implementation costs and the returns to learning-by-doing in process technology following robot adoption can divert resources away from product innovation. Furthermore, robots – even when flexible – might display enabling capabilities only when introduced in flexible production processes. More 'classic' and standardised mass production processes might not benefit from robots' full potential. However, even in mature industries with dis-economies of scope, large investments in machinery can induce a re-structuring of the production process, and influence talent and absorptive capacity formation – all changes that can reduce the negative impact we identify, as they can have spillover effects on product innovation. We take a step further by discussing whether the types of robots under analysis are the 'right' robots to induce innovation. In fact, not all instances of process mechanisation and robotic equipment might be malleable enough to shape technological opportunities and to affect the incentive to engage in new product discovery, design, and development.

The paper is organised as follows: Section 2 provides a literature review that explores the main stylised facts of robotisation and juxtaposes three broad strands of research to construct a framework to guide the discussion of our results. Section 3 describes the data and the methodology we employ. Section 4 presents the results and Section 5 offers a discussion of the mechanisms that might be producing them. Section 6 concludes the paper.

2. Relevant Literature

The focus of our analysis is on robot technology, which is increasingly under the spotlight for its applications, and lately even for being a strategic asset (Nolan 2021). Wirkiermann (2022) outlines the distinction between mechanisation (in the 19th century), computer-based automation (in the 1980s) and contemporary robotisation. The importance of robots, or telerobots (Sheridan 2016), depends on their capacity of automating routine tasks and to act as multi-purpose tools – ultimately, to generate productivity gains. Robots become an interface between humans, control software, and production activities, although, according to the International Federation of Robotics (IFR), the diffusion of highly sophisticated robots that are able to complement human actions (collaborative robots, or cobots) is still very limited worldwide (IFR 2020). Investing in robots answers to different aims, from the reduction of operating costs to the improved resilience in facing positive or negative peaks in production, passing through an increased flexibility and a more efficient use of resources (e.g. energy). In addressing these multifaceted firms' needs, they reconfigure the very set of actions firms can engage into. As a consequence, robots might also be characterised by enabling capabilities.

Despite the interest around robot technology, economists' understanding of their technical features and patterns of adoption is yet limited. One reason for that has to do with the angle of analysis, as most of the literature on recent automation is grounded on theories of routine-biased technical change (Acemoglu and Restrepo 2019), which take occupations and job tasks as key units of analysis but lack in-depth, 'engineering' knowledge on robots as complex technology systems. A second, related reason has to do with data availability at a level, granular enough to appreciate the heterogeneity of robot technology. However, recent studies are starting to build a less vague picture of the implementation of robot technology into production activities. Focusing on German plant-level information, Deng et al. (2021) outline stylised facts of robot adoption, among which, the fact that robot use is relatively rare, the distribution of robots is highly skewed, and that robot adopters are 'exceptional' actors – that is, larger, with higher labour productivity, investing and exporting more and using more novel technology compared to non-robot-using plants. Benmelech and Zator (2022) confirm that robot adoption is yet limited, especially when compared to digital technologies.

We build a framework for our analysis by bridging three different strands of literature that provide relevant insights: i) studies on firm-level automation; ii) studies on the relationship between product and process innovation strategies; and iii) research on the enabling effect of the adoption of emerging technologies on innovative activities.

Firm level analysis of automation and robotisation. As it is the case for more aggregate-level research, firm-level studies of automation and robotisation have focused almost exclusively on labour market impacts. Humlum (2019) uses an event-study approach (on Danish administrative data) to measure worker heterogeneity in exposure to robot adoption. Similarly, Bessen et al. (2020) and Domini et al. (2021) study automation spikes and job separation rates for Dutch and French firms, respectively. Dauth et al. (2021) measure exposure to industrial robots for Germany apportioning data from the IFR using a regional labour market approach combined with worker-level administrative data; Dottori (2021) conducts a similar exercise for Italy. As pointed out by Acemoglu et al. (2020), new firm-level analysis introduces new issues as well. In particular, the detection of a productivity effect of robots can be, in reality, the result of a selection effect: as firms adopting robots reduce production costs, they tend to gain market shares. Overall, employment gains or losses will then be a result of reallocation. In fact, when aggregating firm-level effects, the impact on total employment seems limited to composition effects, with the negative or positive impact of automation on the labour share depending on the magnitude of labour share reduction in the few, usually large, robot-adopting firms (Autor et al. 2020).

Exploiting more granular information, firm-level automation research began to go beyond effects on employment and to focus on the impact of robots on various indicators of performance.

Kromann and Sorensen (2019) use survey data from Danish firms to relate automation measures and performance, measured as labour productivity and profit to sales ratio, finding a positive relationship. Acemoglu et al. (2020) find that French robot adopters experience an increase in value added and productivity beyond a decline in the labour share. Aghion et al. (2020) measure the impact of automation technology (captured by expenditures on industrial equipment and machines or plant-level energy consumption to proxy 'motive power') on French manufacturing firm's employment, wages, prices and profits with an event study and a shift-share setup. They find that next to a positive effect on employment, profits and sales increase while consumer prices decrease. Exploiting the ESEE dataset we also use, Koch et al. (2021) confirm that robot adopters are exceptional in the sense that those firms that are ex ante larger, more productive and exporting have higher likelihood of adopting robots (with a higher likelihood for less skill-intensive firms). Robot adoption boosts output, TFP growth, and exporting. Using import data on industrial robots for French firms, Bonfiglioli et al. (2020) produce additional evidence that robot adopters differ from non-adopters ex ante, being these larger, more productive firms and employing a higher share of managers and engineers. Interestingly, they find that demand shocks lead firms both to expand (increasing employment) and automate; hence, they stress the possibility that a spurious correlation exists between automation and impact on employment. Sudekum et al. (2020) combine industry-level (IFR) data on robot adoption with firm-level information for European manufacturing to study changes in the distribution of sales, productivity, markups, and profits within industries. They find that robotisation disproportionately benefits top firms, reinforcing the trend of emergence of superstar firms (Autor et al. 2020). The authors outline the possibility that robot adoption might slow down knowledge diffusion from frontier firms to laggards, or that superstar firms could be more successful in attracting high-quality labour capable of speeding-up the implementation of the new technology.

Relationship between product and process innovation. A second strand of research that is relevant for our analysis is the economics and strategy literature on the relationship between product and process innovation or R&D activities. Traditionally, the two types of innovations have been analysed individually because of the different strategies underpinning them, which in turn answer to different internal and external stimuli: when competition is driven by high product differentiation, it is optimal to choose a product innovation strategy; when competition is mainly price driven, it is optimal to go for process innovation (Weiss 2003). Only recently, product and process innovation have been studied as strategic complements at the company level. For example, complementarities between process and product innovation are likely to emerge in the so-called process industries, where it is also more appropriate to hypothesise a relation going from process to product (Hullova et al. 2016). Theoretically and more in general, Lambertini (2003) finds that, for a monopolist, cost-reducing process R&D and product innovation are substitutes, as surplus is extracted either by reducing marginal cost for a given number of product varieties, or expanding variety for a given level of production costs. Lin (2004) contrasts this, showing that process and product R&D are negatively related only if the degree of economies of scope in process R&D is low; otherwise, cost-reducing R&D is a positive function of product variety. Mantovani (2006) finds that monopoly profits are higher when product and process strategies are jointly pursued, with initial conditions determining the share of product vs process R&D. In a dynamic setting, Lambertini and Mantovani (2009; 2010) find that process and product innovation are substitutes for a monopolist at any stage of the path towards the steady state equilibrium, and complementary in the steady state. Li and Ni (2016) identify in the learning-by-doing rate (hence, knowledge accumulation regime) for product and process innovation a key parameter deciding whether the two activities are substitutes or complements.

Studies on industry dynamics and evolution, and in particular those mapping industry life-cycles, illustrate the endogenous process leading firms to transition from a focus on product innovation to one on process innovation (Klepper 1996). Cohen and Klepper (1996a) show that the allocation of resources to process or product R&D vary with firm size: process innovation induces less direct sales growth as they cannot be easily sold in disembodied form compared to products. Hence, smaller growth-oriented firms will see higher return in conducting product R&D. As returns to process R&D depend on current output, firms growing larger will tend to shift to process R&D. Bennet (2020) suggests that automation is pursued with higher intensity by either leading firms or laggards depending on the nature of competition and the state of the market. In growing markets, cost-spreading incentives favours incumbents' automation, as these are usually companies capable of bearing high fixed costs of process innovation by spreading them over large quantities produced. In non-growing markets, automation can be driven by market stealing incentives on the side of the laggards, which hope to gain market shares at the cost of the leading firms. In both cases, the takeaway message is that automation decisions are driven by a logic of 'competition for the market', and seem to be independent from product innovation choices.

Empirically, Hirvonen et al. (2022) use text data to explore the product vs process tension by analysing the impact of advanced technology adoption in Finnish manufacturing firms. In their paper, advanced manufacturing technologies include computerised numerical control (CNC) machines, (welding) robots, laser cutters, surface-treatment technologies, measurement devices, enterprise resource planning (ERP), and computer-aided design (CAD) software. Rather than replacing workers, these technologies are adopted to boost competitive advantage; adoption of new tools lead to an expansion in product variety. These findings go in line with the expectation of an enabling capability of advanced manufacturing technologies, among which potentially robots. However, firms involved in the analysis are mostly smaller and medium enterprises that - as pointed out by Cohen and Klepper (1996a) – have 'by design' a higher incentive to engage in product innovation compared to process innovation.

Emerging technologies and innovative activities. A third piece of the framework we are building consists of literature relating the use of novel technologies and innovation behaviour. The idea that certain technologies shape the incentive to innovate in related technologies or industries is at the core of the literature on general-purpose technologies (Bresnahan and Trajtenberg 1995), in which core upstream technologies and downstream technologies that make use of the core ones have linked payoffs in R&D investments. Some technologies are what Koutrumpis et al. (2020) call ‘invention machines’ - what Griliches (1957) identified as ‘invention of a method of inventing’ (IMI) - as “they alter the playbook of innovation where they are applied” (Cockburn et al. 2019). Innovations (inventions) that spur further innovation (inventions) usually feature some elements of multi- or general-purpose, or a ‘meta-technology’ nature (Agrawal et al. 2019). Being multi-purpose malleable tools, robots are a good candidate for the role.

Applied literature on the impact of ICT also detected how enabling technologies open new room for actions at the firm level, resulting in higher productivity (Brynjolfsson and Hitt 2000). More recently, Brynjolfsson et al. (2021) find that a similar effect can be registered in firms adopting predictive analytics techniques. Focusing on Canadian firms, Dixon et al. (2021) find that robot adoption leads to a different type of ‘innovation’, namely changes in organisational structure: using robots produces a reduction in the number of managers but an increase in the span of control for those managers that survive the change. At an even more detailed level of analysis, Furman and Teodoridis (2020) show how the automation of a research task in computer vision and motion sensing research - achieved with the introduction of the Kinect technology - impact subsequent research productivity and type of research output, increasing the production of new ideas as well as their diversity.

Closer to the focus of our analysis, Liu et al. (2020) relate the number of industrial robots (which they use to proxy artificial intelligence) and technological innovation at the industry level, using Chinese panel data for the manufacturing sector. While the coarse data structure does not permit to clearly identify the mechanism at work, the authors find a positive relationship between robots and innovation (measured as patents count), with a stronger effect for low-tech industries. Niebel et al. (2019) observe the relationship between use of big data analytics and product innovation at the firm level, for a sample of manufacturing and service companies from the German ZEW ICT survey and Community Innovation Survey. By reducing uncertainty and supporting decision-making with high-quality information, the expectation is that big data analytics would help innovative activities. The authors find that the use of these techniques raises both the propensity to innovate as well as innovation intensity (measured as the share of sales from new products and services).

The enabling capability of an emerging technology more narrowly defined is studied in Rammer et al. (2021), who focus on a set of artificial intelligence (AI) technologies. The authors use the 2018 module of the German section of the Community Innovation Survey to study the relationship between the use of AI in firms and product and process innovation. While AI is used by a very small share of firms, those adopting AI (and, in particular, the firms that contribute with in-house efforts to the development of AI solutions) use it to innovate, especially product innovations that are new to the market. The analysis is limited by the cross-section nature of the data, but it is useful to shed light on the fact that only certain specific technologies have enabling capabilities.

In summary, linking three strands of literature we have at hand a rich picture of the profile of robot adopters, as well as of the impacts following the adoption of robot technology. First, firm-level studies of automation and robotisation find evidence of self-sorting: adopters are already better performing firms before automation, and automation provides a further boost to performance. Second, whether robots are used only as a process technology or also with the goal of upgrading product offering depends on the forces set in motion by robotisation inside the firm, e.g. adjustment of production, learning, changes in market strategy. Third, the enabling capability of a technology might depend on its very technical features: software technologies such as AI or advanced ICTs such as predictive analytics can be used as a supporting tool to reduce uncertainty and to guide innovation resource allocation decisions. Taken all together, it is possible that robot technology might help to experiment with new product designs and prototypes given its malleability; however this capability might be a feature of a subset of robots only, or one companies are not able or willing to exploit fully.

3. Data and Empirical Strategy

Our analysis covers the period 1991-2016, a period during which there have been significant transformations in the processes of production of firms worldwide. Industrial robots played an important part in these changes. Acemoglu and Restrepo (2020) provide evidence of a fourfold rise in the stock of (industrial) robots in the United States and western Europe between 1993 and 2007, while Graetz and Michaels (2018) show the dramatic fall in robot prices, which halved (and decreased even more when quality-adjusted) roughly in the same period for a sample of six advanced economies.

The adoption of robots has been quite heterogeneous among countries in the last decades (OECD, 2019). Spain, which in 2019 was still the 11th country worldwide for installation of industrial robots (number of robots per 10000 employees), has a specific trend in robotisation. Notably, it has experienced a surge of operational robots adoption by a factor of five in the period 1993-2000, mostly due to the large diffusion of automation in the automotive industry.

For our analysis, we draw on longitudinal firm-level data from a survey of Spanish manufacturing companies: the *Encuesta Sobre Estrategias Empresariales* (ESEE, Survey on Firm Strategies). ESEE covers a rich set of firm-level information over a long time period (1990-2016 to date). ESEE is a survey carried out annually by the SEPI Foundation[2] and comprising nearly 2,000 Spanish manufacturing companies. Previous studies have highlighted how ESEE data cover approximately 22% of total Spanish employment in manufacturing and that there is a bias towards large companies, as it covers the full population of manufacturing firms with more than 200 employees, whereas only a representative sample of SMEs (between 10 and 200 employees) is covered (Barrios et

[2] https://www.fundacionsepi.es/investigacion/esee/en/spresentacion.asp (last accessed 10 April 2022)

al. 2003; D'Agostino and Moreno 2019). ESEE has been extensively employed as a data source for applied studies in economics and management at the firm level.[3]

The ESEE questionnaire includes information on a wide range of topics, such as market and product characteristics, financial data and production activities. For the purpose of our research, ESEE data is ideal because it contains: (i) information on the adoption of industrial robots for firm day-to-day production activities; and (ii) information on firm's product innovation activities. Several variables within ESEE data are collected every four years and refer to the previous three/four-year period. Our final sample entails 3,304 firms in the seven relevant periods between 1991 and 2016 (1991-1993, 1994-1997, 1998-2001, 2002-2005, 2006-2009, 2010-2013, and 2014-2016).

Our aim is to assess the association of robotisation and product innovation performance. For sake of simplicity, we write our relation of interest as follows:

$$ProductInnovation_{it} = \beta Robot_{it} + \gamma \boldsymbol{X_{it}} + \alpha_i + \tau_t + \epsilon_{it} \qquad (1)$$

Product innovation is captured in different ways throughout our empirical analysis. The first two variables measuring product innovation at the firm level are very much in line with the measures employed by a large part of the literature and available from the Community Innovation Survey (CIS) (e.g. Ballot et al 2015; Frenz and Prevezer 2012). Respondent firms were asked whether they introduced new (or significantly improved) product innovations and the number of these product innovations. Operationally, we define the probability of introducing a product innovation as a dummy variable taking value one if this happened at least once during the relevant four-year period, and zero otherwise. Similarly, the number of product innovations is measured as the average number of product innovations over each four-year period. Given the highly skewed nature of the variable, we employ its naturally log-transformed value. In an attempt to measure different nuances of product innovation, we employ three indicator variables capturing (in a binary way) whether product innovation is due to: (i) the introduction of new materials; (ii) the introduction of new parts or intermediate products or (iii) the introduction of new product functions.

$Robot_{it}$ is a variable measuring whether firm i has adopted any industrial robot in period t. Following Koch et al. (2021), we construct an indicator variable equal to one if the firm uses robots and zero otherwise. Information for this variable is available every four years, starting in 1991.

In Equation 1, $\boldsymbol{X_{it}}$ is a vector of time varying characteristics of the firm that can affect product innovation performance and may be associated with the decision to adopt robot technologies. The inclusion of this vector allows controlling for omitted variable bias driven by the observables. Furthermore, this allows us to control for variables related to the impact of the industry life-cycle on

[3] For a comprehensive list of publications see https://www.fundacionsepi.es/investigacion/esee/en/sesee_articulos.asp (last accessed 10 April 2022)

innovation, as discussed in the literature review. More in details, we control for a set of firm-level characteristics including firm size, measured as the average number of full-time equivalent employees in the relevant four-year period. We also include two measures of investment. First, we measure the total expenditure in R&D as the sum of intra- and extra-mural expenditures in the period. Second, we include the investment in industrial machinery. Both measures have been deflated by using the industry-level consumer price index provided by the Spanish statistical office (instituto nacional de estadística) (with 2015 as base year). In addition, we control for the share of foreign ownership (both as direct and indirect foreign capital participation) over the relevant time period. We also account for the exposure of the firm to international markets by including the share of the total value of exports over sales in the relevant period. Finally, we introduced a set of period fixed effects controlling for time varying shocks which can jointly affect the firms in our sample (e.g. business cycle effects). All the controls have been lagged by one year to mitigate reverse causality problems and have been transformed in natural logarithms. The coefficient α_i captures the time invariant firm heterogeneity that may be associated to both automation and innovation performance and is generated also by unobservable factors, like managerial orientation and baseline productivity. With τ_t we also control for time shocks that are common to all the firms in our sample.

The parameter of interest β captures the impact of robotisation on the probability to introduce a product innovation and on the (log transformed) number of product innovations, our core dependent variables. We estimate Equation 1 with a linear model, which amounts to a linear probability model when the dependent variable is binary.

We account for the fact that robotisation can have an impact on the innovation of the firm over a longer time period which extends beyond its immediate implementation – as robot adoption might induce a dynamic reconfiguration of firm processes, incentives and, thus strategies, in the medium and long run. In light of this, we estimate different versions of Equation 1, which include the lagged adoption of robot technologies (with a 4-year and an 8-year time lag).

Drawing from Koch et al. (2021) we improve our analysis accounting for the fact that robot-adopters may be systematically different from non-adopters. Table 1 reports some descriptive statistics on relevant characteristics across the two groups (adopters vs non-adopters). As expected, differences are relevant and always statistically significant. Similarly, to what has been identified in the literature (Deng et al. 2021), firms adopting robots tend to innovate more in products, are larger, invest more in machinery and R&D and are more internationalised.

[TABLE 1 ABOUT HERE]

In order to better control for selection bias into adoption of robot technologies, we rely on a model with leads and lags under a difference-in-difference approach. Building upon established approaches, we estimate a two-way fixed effects (TWFE) model with leads and lags (distributed-lag model) which controls for a treatment occurring at different points in time (Angrist and Pischke 2008; Autor 2003; Cerulli and Ventura 2019; Cheng and Hoekstra 2013). Notably, we estimate the following model:

$$ProductInnovation_{it} = \beta_{+4}Robot_{it+4} + \beta_0 D_{it} + \beta_{-4}Robot_{it-4} + \beta_{-8}Robot_{it-8} + \gamma \boldsymbol{X_{it}} + \mu_i + \tau_t + \epsilon_{it} \quad (2)$$

In Equation 2, β_{+4} captures the effect of robotisation one period (i.e. 4 years) before it actually occurs. In other terms, β_{+4} denotes the anticipation effect of robotisation. β_{-4}, and β_{-8} capture the lagged effect of robot adoption, in other terms the effect of robots one and two periods (4 and 8 years)[4] after the adoption. All in all, the diff-in-diff approach that we implement combines the capacity to control for group differences (driven by unobservables) between adopters and non-adopters, observable characteristics of the firm and unobservable time invariant features that are captured by individual fixed effects. Standard errors are clustered at the firm level. We also test for the parallel trend assumption by checking whether the lead is not different from zero (our H_0). If we fail to reject the null hypothesis: this would suggest that before the treatment the adopter and the non-adopters were subject to common trends conditional on observable and unobservable characteristics.

Although the TWFE estimator has been standard practice in the applied econometrics literature in the past decade, recent developments have shown that this may be biased in the presence of time-varying treatment effects (Cunningham 2021; Goodman-Bacon 2021). Hence, our estimation strategy could report biased estimates due to the different timing of adoption of robot technologies in our sample of companies (between 1994 and 2014), particularly if the type of robots adopted were different in nature or the firms self-selecting into robot adoption are extremely different depending on the year of adoption. Additional complications can be posed by the presence of reversals: firms that during the full period of observation switch in and out of robot adoption. In order to address said issues and provide robustness to our results, in a set of robustness checks we implement a recent estimator proposed by De Chaisemartin and d'Haultfoeuille (2022). This is one of the most flexible event study estimators to date, as it allows for treatment switching (units can move in and out of treatment status) in addition to time-varying, heterogeneous treatment effects. Reassuringly, as will discuss in the next section, our core results are confirmed.

[4] The first (1991-1993) and the last time window in our dataset (2014-2016) cover a three-year time span each instead of a four-year window. While the first covers by construction of the ESEE survey a three-year time span, we have to rely on a three-year window for the last window due to the lack of available data for the fourth year at the time of the writing.

4. Results

At the outset, we provide evidence from standard fixed effect estimations. Table 2 focuses on the effect of robotisation on the probability to introduce a product innovation. We investigate the effect of robotisation at time *t,* as well as the effect of a lagged (4- and 8-year) adoption of robots. As far as the controls are concerned, once controlling for unobserved heterogeneity, R&D expenditure emerges as the only predictor that is exerting a positive and significant effect across the different specifications. On average, a 1 percent increase in R&D expenditure is associated with a 2.5-2.7% increase in the probability to introduce product innovations. When turning our attention to the effect of robotisation, we notice two main aspects. First, the effect of robotisation is not immediate, but emerges after 4 (Column 2) or 8 (Column 3) years. Second, the effect of robotisation is detrimental for the probability of introducing a product innovation.

[TABLE 2 ABOUT HERE]

A less clear picture emerges when we consider the other main dependent variable, i.e. the log transformed number of product innovations introduced by the firm in a 4-year period (Table 3). Here we notice a general loss of significance, especially for the 4-year lagged robotisation while the 8-year lagged adoption is only barely insignificant at the conventional thresholds (p-value of 0.106). Combining what emerges from Table 2 and Table 3, it seems that the adoption of robot technologies does not trigger innovation. In fact, when looking in particular at the proclivity of introducing new products, we notice that this seems to be reduced as a result of robot adoption. We also observe that the adoption of automation technologies takes time to exert an impact.

[TABLE 3 ABOUT HERE]

As mentioned in Section 3, our empirical analysis which is based on a TWFE estimator benefits from the possibility to control for systematic (unobservable) differences between adopters and non-adopters of robot technologies. Results shown in Table 4 enrich the evidence coming from the standard fixed-effects regressions. In particular, when focusing on the impact on the probability to introduce a product innovation (Column 1) we confirm the negative effect of robotisation, which consolidates and gets more significant as we consider longer time lags. The adoption of robot technologies decreases the probability to conduct product innovation by 9.3% 8 years later. Similarly, robotisation is found to have a negative impact on product innovation, when the latter is captured through the number of new products introduced in a four year period (Column 2). On average, robot adoption decreases, after 8 years, the number of new products introduced into the market by 0.15%. This is consistent with the fact that robotisation is found to contract the innovative effort of the firm, captured by the R&D investment (Column 3). On average, the adoption of robot technologies is associated with a 0.85% decrease in R&D spending 8 years later.

[TABLE 4 ABOUT HERE]

In Table 5, we are able to provide a closer look at the effect of robotisation on the probability to introduce different types of product innovation. While leaving unaffected the introduction of products with new material (Column 1), results show that again after a certain amount of time (at least 8 years) the adoption of robot technologies reduces the probability that the firm introduces different types of new products, which are characterised by new components (Column 2) or new functions (Column 3).

[TABLE 5 ABOUT HERE]

Finally, in order to delve more deeply in the analysis of the relation between robotisation and product innovation strategy we ran our estimates resorting to a proxy for the magnitude of robot adoption. Our aim is to check whether the size of the investment in robotisation affects its relation with firm innovation. In particular, drawing on Aghion et al. (2020), we exploit the information on the size of investment in machinery to infer whether robotisation is a small- or large-scale one. We flag small-scale robotisation when the adoption of robots coincides with an investment in industrial equipment within the first quartile, while large-scale robotisation refers to investment in industrial equipment in the last quartile of the distribution. In the case of small-scale investment (Table 6), we observe the same results described above, where robotisation is reducing firm innovation in the long run, as well as R&D. For large-scale investment (Table 7), we continue to find no enabling effect on product innovation. Nevertheless, we note the disappearance of the significance associated with the negative coefficient. We also find a positive and significant effect that large-scale investment seems to exert on the R&D investment of the firm. The increased R&D expenditure which does not result in an increased innovation seems to suggest that such an innovation effort is aimed at absorbing the changes imposed by the implementation of novel automated production processes.

[TABLE 6 ABOUT HERE]

[TABLE 7 ABOUT HERE]

As mentioned in Section 3, we check for the robustness of our results when accounting for the time-varying treatment (i.e. robotisation) effects as well as for the fact that the treatment (i.e. robotisation) may be heterogeneous across time periods and for the possible issues arising from the presence of treatment-switchers or reversals (e.g. Cunningham 2021; Goodman-Bacon 2021; de Chaisemartin and d'Haultfoeuille 2022). Table A1 in the Appendix confirms the heterogeneity across firms' cohorts in the adoption of robot technologies. Figures A1-A4 graphically report the results emerging from the estimator developed by de Chaisemartin and d'Haultfoeuille (2022). These largely confirm our evidence. The adoption of robot technologies is significantly and negatively associated to the probability of product innovation and the number of new products introduced into the market (Figure 1). Robust results also emerge for the different types of product innovation introduced (Figure 2). Similarly, Figure 3 and 4 confirm the evidence presented above for the effect of small- and large-scale investments on innovation outputs (both in terms of probability and number of innovations). While Figure 4 confirms the effect on R&D for large-scale investments too, we observe that the association between the adoption of robots and investment in R&D, albeit with a negative sign, loses significance in the baseline regressions (Figure 1 – bottom left panel) and for small-scale investment (Figure 3 – bottom left panel).

5. Discussion

We advance some arguments to rationalise our findings. These insights are meant to highlight some general mechanisms at work in the interplay between process and product innovation, as well as to guide further analysis.

Robot adoption influences the process-product innovation trade-off. A first argument is that robotisation and product innovation might be processes running in parallel, responding to different strategic logics and incentives within a firm. Robotisation as process innovation aims at cost reduction and can be driven by cost-spreading incentives (Cohen and Klepper 1996b). Furthermore, it can be seen as an instantiation of localised technical change (Atkinson and Stiglitz 1969): hence, its impact might be confined to the organisation of operations along the production process (Hopp and Spearman 2011) without spilling over to other firm activities. Instead, a product innovation strategy responds to the logic of value creation and capture. While being related to different strategic levers, the two activities compete for the same pool of resources inside a firm. This can turn product and process innovation decisions into substitutes. In fact, in our data, a negative relationship between robotisation and product innovation emerges in the medium and long run. Given limited (financial, managerial, time) resources, firms solve an allocation problem choosing between two alternative strategies, namely whether to purchase and implement new capital goods such as robots, or to develop new or improved products. In this context, investments as well as management attention dedicated to fine-tune new robotic processes might shift away focus from product innovation. As robot technology is not 'plug-and-play', adoption might require organisation adjustments and the formation of specific capabilities, which might high returns to knowledge accumulation and imply dis-investments from product-innovation-related activities. This argument fits with what is suggested in the model by Li and Ni (2016), where the two activities become substitutes if the rate of knowledge accumulation is higher for process innovation – in our case, after robot adoption. The fact that the negative effects appear a few years after robot adoption takes place could be the result of inertia in absorbing sunk investments (Peters and Trunschke 2021): older product innovation investments, or current investments already planned in the past generate novelties with a delay that overlaps with new process investments. In sum, the trade-off between product and process strategy is hidden for some years, until it starts to 'bite'.

A more indirect circuit through which substitutability can materialise relates to the flows of labour induced by robot adoption. First, the 'learning-by-adopting-robots' effect can direct human capital formation away from tasks related to product innovation. Second, as detected in the literature (Acemoglu et al. 2020), robotisation reduces the overall labour share at the firm level. Potentially, the decrease of labour costs for the factory floor could make room for expanding employment in high-skills functions, including the design and prototyping of new products. However, the outflow of labour might include workers employed in different, non-overlapping activities, including some involved in product innovation. This will happen especially when the task vector composing some occupations feature activities related to both process and product innovation. The migration of talent induced by the adoption of process technology might spill over to loss of talent in product-related tasks: robotisation might improve firms' exploitation capabilities (better processes) while de-skilling them with respect to exploration (new ideas and designs) capabilities.

In our case, considering a substitutive relationship between process and production innovation implies that the more resources are invested in robotisation, the lower the effort allocated to product innovation, even if with a lag. Instead, what our results uncover is a less trivial relationship, which seems to have a piecewise nature: high investment levels in machinery cancel-out the negative impact we identified. If a piecewise substitutive relationship exists, at a high enough level of investments in robots we should expect a relaxation of the trade-off between allocating resources to process versus product innovation, which is precisely what we observe. This suggests the possibility of a *conditional* product-process innovation substitutability. The condition could be the existence of a minimum investment threshold, capturing an essential enabling condition for firms to operate robot process technology while continuing innovating. We do not interpret this threshold in terms of firm size, as we control for this covariate in our empirical setting. Instead, the threshold can be a direct mapping of the rate of accretion of absorptive capacity. As absorptive capacity is often developed through formal innovative activities, as it is one of the 'two faces' of R&D (Cohen and Levinthal 1989), the moderation effect of large investments in mechanisation on product innovation should go hand in hand with an increase in R&D expenditure. This goes very much in line with our findings. Large investments in robotisation might produce economies of learning which compress the time needed for robots' installation, accelerate the absorption of the transaction costs incurred when trialling the new process technology and, thus, make the product-process trade-off less binding.

In summary, robot adoption at a small scale refocuses firms' attention and effort away from product innovation in a persistent way. However, large-scale investments seem to induce a more profound re-organisation of production, which requires the development of absorptive capacity. This leads to increasing R&D expenditures. The resulting economies of learning can spill-over on product innovation activities, cancelling-out the negative impact following the narrowing of attention to process change.

Robots adopted are not flexible enough to enable product innovation. A different take at our results is to factor-in the level of sophistication of robots. The hypothesis that robotisation as process innovation could induce product innovation is grounded on an enabling view of advanced robots in virtue of their malleability. The underlying mechanism would be that flexible production technology counteracts the pressure exerted by dis-economies of scope, making product variety economically and technologically viable.

This will happen only if robots aid variety expansion and product diversification more than they accelerate mass production; otherwise, the prevailing pressure would be to focus capacity on existing product designs, resulting in a stagnation or decrease in product innovation. An interpretation of this mechanism could be in terms of selection in the product portfolio: if robots are flexible enough, they will favour product repositioning; at the same time, they create an incentive for the exit of mature product lines that cannot be refreshed. Automation technology covered in our dataset likely misses the most recent wave of malleable, smart technologies while capturing more traditional process improvements. This is a possibility not limited to our sample: as the IFR (2020) points out, the share of collaborative robots (one the best candidates to the role of malleable equipment) is yet small. Following this argument, the negative baseline impact we detect on product innovation might be due to the fact that we relate inflexible capital goods and product innovation, where the former tends to create production economies only on those product lines that robots are designed to produce. Finally, and in any event, product innovation is not necessarily an outcome of the use of malleable capital goods:

malleability is possibly being used to make a single piece of equipment executing multiple functions in already existing production processes, rather than to experiment with new ones.

6. Conclusion

In this paper, we exploited firm-level data on robot adoption to study the unexplored relationship between robotisation and innovation. As robotisation activities are a case of process innovation in which companies adopt flexible capital goods, our study is essentially assessing the nature of the interplay between recent instances of process and product innovation. Given the features of the current wave of robotisation, one could hypothesise an enabling effect on product innovation, with entry of new varieties, designs, and in general differentiation aided by the availability of smart production tools.

Adopting an event-study approach, instead of an enabling effect, we find that robot adoption produces a persistent negative effect on product innovation, regardless of the indicator chosen to measure it. Interestingly, the size of the investments in mechanisation after a certain threshold cancels-out the negative effect, while exerting a positive effect on R&D expenditure. Following the literature, we rationalise and interpret the findings by exploring different hypotheses. Theory suggests that process and product innovation can be substitutes or complements under different settings. Based on our evidence, we suggest a piecewise substitutive relationship. Large investments relax the product-process trade-off, as substantial R&D investments to accrue absorptive capacity are mobilised, and the learning economies and spillovers they generate make less binding the allocation dilemma between implementing robot technology and designing and trialling new products.

As we detect persistent effects over the medium and long run, structural dynamics might be playing a role beyond trade-offs in strategic allocation of resources. For example, according to industry evolution models (Klepper 1996), the ratio of product to process innovation tends to decrease endogenously as industries and markets transition from birth to maturity. From this angle, robotisation does nothing but reinforce industries' incentive to engage in their 'classic' strategy: exploiting dynamic economies of scale by focusing on cost reduction, which, in turn, allows for capacity expansion over a small set of (standardised) products. However, our empirical setting takes that into account by introducing an extensive set of controls, and, therefore, we rule out this set of explanations.

To our knowledge, this paper is the first expanding the literature on automation to the microeconomics of innovation and firms' strategic decision making. While exploratory in kind, our results suggest that non-linear mechanisms are at work within companies when robots are used to re-organise production activities. It is important to remark that we cannot easily generalise the mechanisms we hypothesised. Spain (the focus of our investigation) is a peculiar context, which experienced a surge of robotisation in the 1990s in large part due investments by the automotive industry following a reorganisation of its supply chain. Hence, a particular attention should be devoted to the country-specific patterns of industrial transformation. Still, we maintain that the non-positive impact of robotisation on product innovation can shed some light on how the most recent phase of mechanisation of production influences other key strategies at the firm level.

Robotisation seems to be capable of breaking a product-process trade-off only in case of very large investments, which capture either the development of capabilities as a requirement as well as by-product of implementation, or the transition towards different (more flexible) modes of production that can reap the fully benefits of flexible robots. It is important to stress that most of the robotisation analysed in our empirical setting belongs to an early wave of robots used in the industrial plants. The specific type of robots adopted do matter. In particular, innovation-inducing robots are those characterised by the feature of being research tools, invention machines, or IMIs. These types of robots are used to aid the search process over, for example, the space of materials to be employed or the space of designs to be trialled and prototyped. Industrial robots such as the majority of those captured by our data might not completely lack the capability to enable new activities; however, they are not IMIs, and have less scope for what concerns facilitating innovation-related search. New IMIs, such as certain types of AI algorithms, are mainly software technologies, which are used in knowledge-intensive domains and are not yet seamlessly integrated in the architecture and functionalities of industrial robots. By contrast, robots are employed in the manufacturing sector to increase the rate of execution and the precision of factory floor tasks under specific conditions (Combemale et al. 2021).

Beyond firm strategy, our analysis has implications for policy. This focus is important and timely, given the many policy packages around the tenets of Industry 4.0 discussed and implemented in different European countries[5]. In general, our results suggests that if the policy goal is to increase rate and direction of innovation, then facilitating equipment acquisition through, for instance, loans or subsidies might not serve the purpose, or even generate unexpected negative effects. Interventions of this kind might succeed only when (i) they are easing the transition to the use of those specific robots that have enabling capabilities and (ii) they are substantial enough in magnitude to allow companies to reach the minimum investment threshold that cancels-out negative incentives to engage in product innovation. Concerning (i), diffusion policies directed at smart robots, collaborative robots and similar flexible technologies should first assess whether firms really demand or seek to deploy this kind of capital goods, in order to avoid resource misallocation. In the case of (ii), policies in this domain might be successful when the interventions are targeted to those actors that cannot reach high investment levels by themselves (e.g. newer and smaller firms), or when they are directed at absorptive capacity formation. Policy makers should be wary of the degree of sophistication of the production technologies, in order to get a sense of the broad direction of the relationship between process and product strategies and, hence, to time actions appropriately. Policies of horizon scanning for new enabling technologies

[5] For example, the financial support for R&D&I in the field of Industry 4.0 in Spain (https://www.mincotur.gob.es/portalayudas/industriaconectada); the Industry 4.0, now Transition 4.0 programme, in Italy (https://www.mise.gov.it/index.php/it/transizione40) (last accessed 10th April 2022).

combined with surveys of firms' needs, as well as policies helping the formation or hiring of skills matching product innovation tasks might be more effective in a context such as the one we studied.

Future research has the task to focus more explicitly on the most recent automation waves, as well as to go more in-depth into the 'nano' dimension of what happens at the factory floor level where robots are implemented, using an 'insider econometrics' approach (Ichniowski and Shaw 2003). Case studies focusing on how malleable capital is embedded into production as well as research and decision processes will help to shed further light on the relationship between robotisation and innovative activities.

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Tables

Table 1. Summary statistics by robot adopters / non-adopters (n=9252)

	Non-adopters *[n=8093]*	**Adopters** *[n=1159]*	**Significance difference test**
Number of product innovations	1.88	3.11	***
	[15.11]	[23.9]	
New product introduction	0.3	0.44	***
	[0.46]	[0.5]	
FTE employees	126.5	342.8	***
	[308.8]	[616.4]	
R&D investment (thous.)	258.23	1156.5	***
	[1700]	[5330]	
Investment in machinery (thous.)	803.5	2705.2	***
	[3706.46]	[8679.64]	
Foreign ownership (%)	11.36	24.82	***
	[29.622]	[40.743]	
Export intensity	0.15	0.27	***
	[0.24]	[0.27]	

Notes: The entries are means and standard deviations of firm level data for the sample used the estimation of equation 1. Test scores report significance levels of i) t-tests on the equality of means for FTE employees, R&D investment, investment in industrial equipment, Foreign ownership and Export intensity; ii) Wilcoxon-Mann Whitney test for the number of product innovations given the non-normally distributed nature of the variable and iii) chi-squared test for new product introduction due to the categorical nature of the variable. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 2. Robotisation and probability of product innovation: fixed effects regression

	(1)	(2)	(3)
Robot	-0.014		
	[0.017]		
Robot t-4		-0.056***	
		[0.021]	
Robot t-8			-0.077***
			[0.030]
R&D Exp	0.027***	0.025***	0.025***
	[0.002]	[0.002]	[0.003]
Size	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]
Export Int	0.083	0.089	-0.036
	[0.070]	[0.085]	[0.116]
Foreign Own	0.003	-0.002	-0.008
	[0.009]	[0.012]	[0.017]
Invest Mach	0.006***	0.004**	0.004
	[0.001]	[0.002]	[0.003]
Constant	0.223***	0.260***	0.255***
	[0.024]	[0.031]	[0.043]
Firm FEs	Inc.	Inc.	Inc.
Time FEs	Inc.	Inc.	Inc.
F	46.666	35.247	22.463
R-sq	0.212	0.229	0.239
N firm-year obs	9339.000	6154.000	3757.000
N firm-year	3299.000	2405.000	1518.000

Notes: Standard errors are clustered at the firm level. Estimation is by the within estimator. The dependent variable is a dummy variable taking value one when the firm introduced new (or significantly improved) products at least once during the relevant four-year period, and 0 otherwise. All regressions include controls for R&D expenditure, firm size, investment in industrial equipment, export intensity, foreign ownership and year dummies. * p<0.10, ** p<0.05, *** p<0.01

Table 3. Robotisation and number of product innovation: fixed effects regression

	(1)	(2)	(3)
Robot	-0.039		
	[0.029]		
Robot t-4		-0.045	
		[0.035]	
Robot t-8			-0.075
			[0.046]
R&D Exp	0.031***	0.026***	0.020***
	[0.003]	[0.003]	[0.004]
Size	0.000	0.000**	0.000
	[0.000]	[0.000]	[0.000]
Export Int	0.059	0.025	0.003
	[0.116]	[0.133]	[0.154]
Foreign Own	0.010	0.000	0.012
	[0.017]	[0.020]	[0.019]
Invest Mach	0.003	0.005	0.002
	[0.003]	[0.003]	[0.004]
Constant	0.230***	0.275***	0.336***
	[0.046]	[0.052]	[0.067]
Firm FEs	Inc.	Inc.	Inc.
Time FEs	Inc.	Inc.	Inc.
F	20.513	15.215	8.473
R-sq	0.125	0.130	0.136
N firm-year obs	9252.000	6131.000	3741.000
N firm-year	3289.000	2400.000	1514.000

Notes: Standard errors are clustered at the firm level. Estimation is by the within estimator. The dependent variable is the log-transformed number of new (or significantly improved) products introduced during the relevant four-year period. All regressions include controls for R&D expenditure, firm size, investment in industrial equipment, export intensity, foreign ownership and year dummies. * p<0.10, ** p<0.05, *** p<0.01

Table 4. Robotisation, product innovation and R&D: lead-lag specification

	(1)	(2)	(3)
Robot t+4	-0.003	-0.027	0.175
	[0.034]	[0.055]	[0.250]
Robot	-0.046	-0.042	0.397
	[0.033]	[0.054]	[0.304]
Robot t-4	-0.047	-0.095	0.343
	[0.038]	[0.058]	[0.331]
Robot t-8	-0.093**	-0.154**	-0.848**
	[0.042]	[0.075]	[0.371]
R&D Exp	0.027***	0.018***	
	[0.004]	[0.005]	
Size	0.000	0.000	0.004***
	[0.000]	[0.000]	[0.001]
Export Int	-0.195	-0.130	1.920
	[0.151]	[0.209]	[1.630]
Foreign Own	-0.014	0.019	-0.283
	[0.027]	[0.034]	[0.190]
Invest Mach	0.002	0.003	0.056
	[0.004]	[0.006]	[0.037]
Constant	0.318***	0.392***	4.060***
	[0.061]	[0.101]	[0.605]
Firm FEs	Inc.	Inc.	Inc.
Time FEs	Inc.	Inc.	Inc.
F	8.153	4.747	2.693
R-sq	0.192	0.083	0.179
N firm-year obs	2304.000	2301.000	2304.000
N firm-year	983.000	983.000	983.000

Notes: Standard errors are clustered at the firm level. Estimation is by TWFE estimator. The dependent variable is the probability to introduce (column 1) and the log-transformed number of (column 2) new (or significantly improved) products during the relevant four-year period and R&D expenditure (column 3). Regressions in columns 1-2 include controls for R&D expenditure, firm size, export intensity, foreign ownership and year dummies. Regression in column 3 include controls for firm size, investment in industrial equipment, export intensity, foreign ownership, firm and year dummies. * p<0.10, ** p<0.05, *** p<0.01

Table 5. Robotisation and different types of product innovation: lead-lag specification

	(1)	(2)	(3)
Robot t+4	-0.017	0.033	0.013
	[0.033]	[0.028]	[0.030]
Robot	-0.006	-0.033	0.008
	[0.035]	[0.032]	[0.030]
Robot t-4	0.025	0.007	-0.029
	[0.036]	[0.034]	[0.036]
Robot t-8	-0.042	-0.075**	-0.116***
	[0.037]	[0.038]	[0.035]
R&D Exp	0.014***	0.016***	0.016***
	[0.003]	[0.003]	[0.003]
Size	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]
Export Int	0.151	0.062	0.039
	[0.138]	[0.142]	[0.141]
Foreign Own	0.006	0.014	-0.013
	[0.022]	[0.021]	[0.024]
Invest Mach	0.002	0.002	0.002
	[0.003]	[0.003]	[0.003]
Constant	0.099*	0.116**	0.135**
	[0.056]	[0.052]	[0.059]
Firm FEs	Inc.	Inc.	Inc.
Time FEs	Inc.	Inc.	Inc.
F	3.458	3.748	4.355
R-sq	0.117	0.145	0.160
N firm-year obs	2304.000	2304.000	2304.000
N firm-year	983.000	983.000	983.000

Notes: Standard errors are clustered at the firm level. Estimation is by TWFE estimator. The dependent variable is whether the firm introduced products with new (or significantly improved) materials (column 1), components (column 2) or functions (column 3) during the relevant four-year period. All regressions include controls for R&D expenditure, firm size, investment in industrial equipment, export intensity, foreign ownership, firm and year dummies.* p<0.10, ** p<0.05, *** p<0.01

Table 6. Robotisation, product innovation and R&D: small-scale investment (bottom quartile)

	(1)	(2)	(3)
Robot_p25 t+4	0.029	-0.014	0.200
	[0.053]	[0.035]	[0.254]
Robot_p25	-0.024	-0.053	0.287
	[0.063]	[0.035]	[0.365]
Robot_p25 t-4	-0.086	-0.065	0.323
	[0.065]	[0.041]	[0.348]
Robot_p25 t-8	-0.166**	-0.099**	-0.732*
	[0.073]	[0.042]	[0.394]
R&D Exp	0.016***	0.026***	
	[0.005]	[0.004]	
Size	0.000	0.000	0.004***
	[0.000]	[0.000]	[0.001]
Export Int	-0.126	-0.185	1.629
	[0.213]	[0.152]	[1.659]
Foreign Own	0.017	-0.014	-0.285
	[0.034]	[0.027]	[0.191]
Invest Mach	0.003	0.003	0.058
	[0.006]	[0.004]	[0.037]
Constant	0.376***	0.310***	4.088***
	[0.103]	[0.061]	[0.610]
Firm FEs	Inc.	Inc.	Inc.
Time FEs	Inc.	Inc.	Inc.
F	5.023	7.869	2.268
R-sq	0.054	0.085	0.033
N firms	978.000	978.000	978.000

Notes: Standard errors are clustered at the firm level. Estimation is by TWFE estimator. The dependent variable is the probability to introduce (column 1) and the log-transformed number of (column 2) new (or significantly improved) products during the relevant four-year period and R6D expenditure (column 3). Regressions in columns 1-2 include controls for R&D expenditure, firm size, export intensity, foreign ownership and year dummies. Regression in column 3 include controls for firm size, investment in industrial equipment, export intensity, foreign ownership, firm and year dummies. * p<0.10, ** p<0.05, *** p<0.01

Table 7. Robotisation, product innovation and R&D: large-scale investment (top quartile)

	(1)	(2)	(3)
Robot_p75 t+4	0.062	0.053	0.658
	[0.083]	[0.058]	[0.403]
Robot_p75	-0.077	-0.041	0.806*
	[0.095]	[0.061]	[0.470]
Robot_p75 t-4	-0.103	-0.073	0.700*
	[0.076]	[0.065]	[0.396]
Robot_p75 t-8	-0.099	-0.029	-0.583
	[0.109]	[0.062]	[0.550]
R&D Exp	0.017***	0.027***	
	[0.005]	[0.004]	
Size	0.000	0.000	0.003**
	[0.000]	[0.000]	[0.001]
Export Int	-0.111	-0.179	1.513
	[0.211]	[0.152]	[1.659]
Foreign Own	0.023	-0.011	-0.307
	[0.036]	[0.028]	[0.194]
Invest Mach	0.003	0.002	0.053
	[0.006]	[0.004]	[0.038]
Constant	0.358***	0.295***	4.247***
	[0.100]	[0.062]	[0.622]
Firm FEs	Inc.	Inc.	Inc.
Time FEs	Inc.	Inc.	Inc.
F	5.482	8.345	2.403
R-sq	0.051	0.084	0.036
N firms	978.000	978.000	978.000

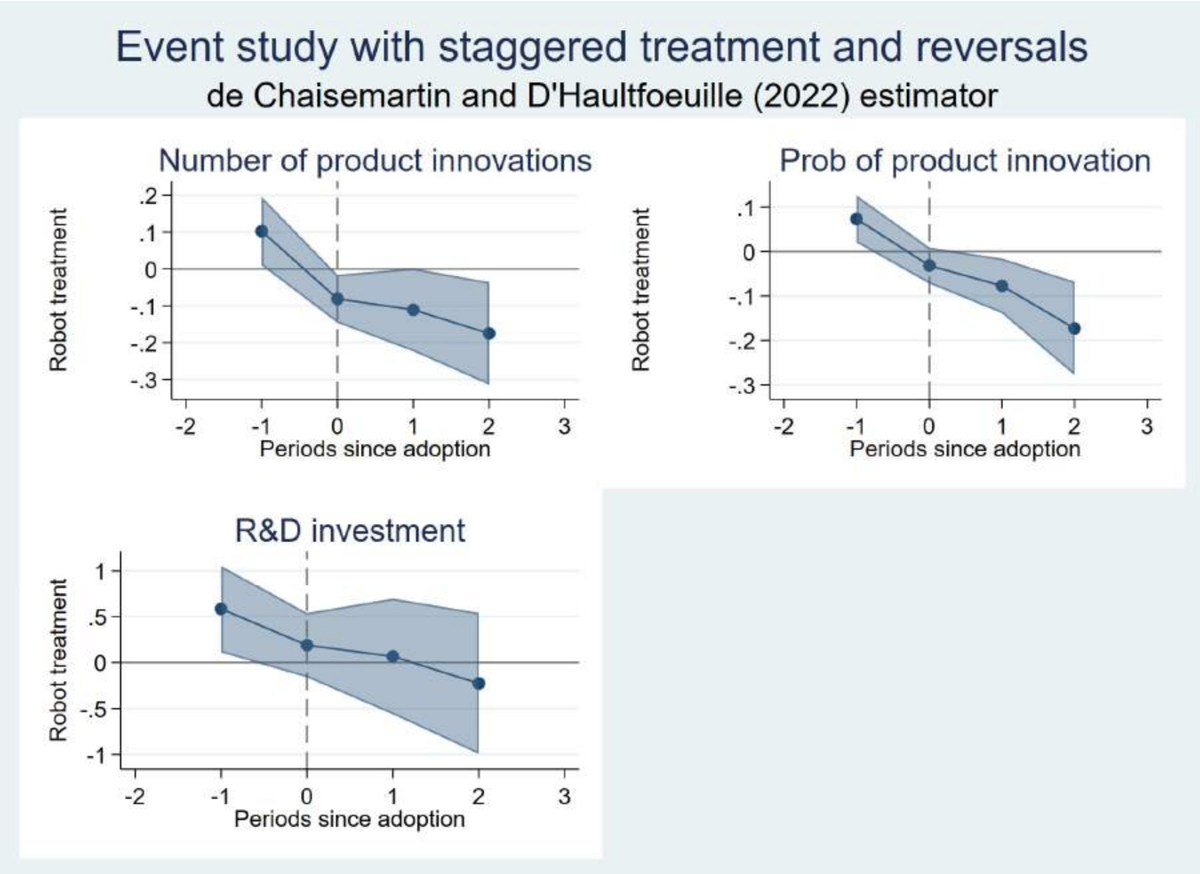
Notes: Standard errors are clustered at the firm level. Estimation is by TWFE estimator. The dependent variable is the probability to introduce (column 1) and the number of (column 2) new (or significantly improved) products during the relevant four-year period and R6D expenditure (column 3). Regressions in columns 1-2 include controls for R&D expenditure, firm size, export intensity, foreign ownership and year dummies. Regression in column 3 include controls for firm size, investment in industrial equipment, export intensity, foreign ownership, firm and year dummies. * p<0.10, ** p<0.05, *** p<0.01

Appendix

Table A1. Descriptive statistics by year of adoption of robot technologies

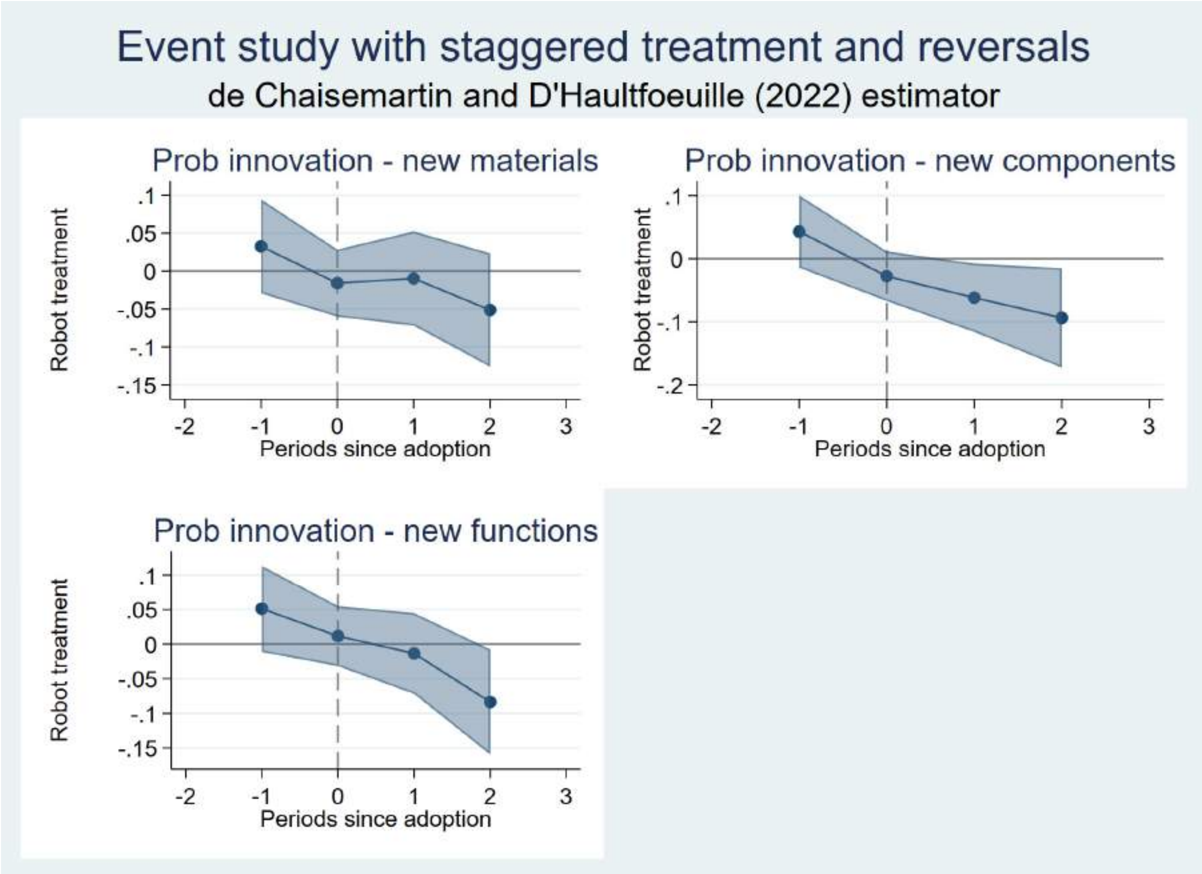
	1994	**1998**	**2002**	**2006**	**2010**	**2014**	**Total**
	n=116	*n=189*	*n=207*	*n=210*	*n=256*	*n=181*	*n=1159*
Number of product innovations	6.00	8.00	1.69	1.70	2.04	0.90	3.11
	[37.9]	[46.37]	[8.35]	[6.51]	[15.18]	[3.92]	[23.9]
New product introduction	0.69	0.62	0.4	0.41	0.35	0.29	0.44
	[0.46]	[0.49]	[0.49]	[0.49]	[0.48]	[0.46]	[0.5]
Investment in machinery (thous.)	2666.40	4254.98	3456.57	3481.27	1293.05	1349.50	2705.22
	[6085.34]	[8979.87]	[9263.54]	[14663.57]	[3088.24]	[2615.56]	[8679.64]
R&D investment (thous.)	988.08	1437.08	1246.07	791.69	1065.94	1420.43	1156.51
	[3522.28]	[4889.44]	[4857.64]	[3841.7]	[6047.28]	[7322.72]	[5330.72]
FTE employees	447.81	481.28	384.47	323.14	242.84	247.25	342.77
	[784.31]	[824.68]	[657.31]	[620.21]	[358.31]	[406.24]	[616.41]
Export intensity	0.24	0.28	0.27	0.26	0.26	0.31	0.27
	[0.22]	[0.26]	[0.27]	[0.27]	[0.28]	[0.3]	[0.27]
Foreign ownership (%)	28.72	29.26	30.04	23.28	21.61	18.06	24.82
	[41.21]	[41.82]	[43.89]	[40.88]	[39.32]	[36.15]	[40.74]

Figure A1. Robotisation and product innovation: de Chaistemartin and D'Haultfoeuille (2022) estimator



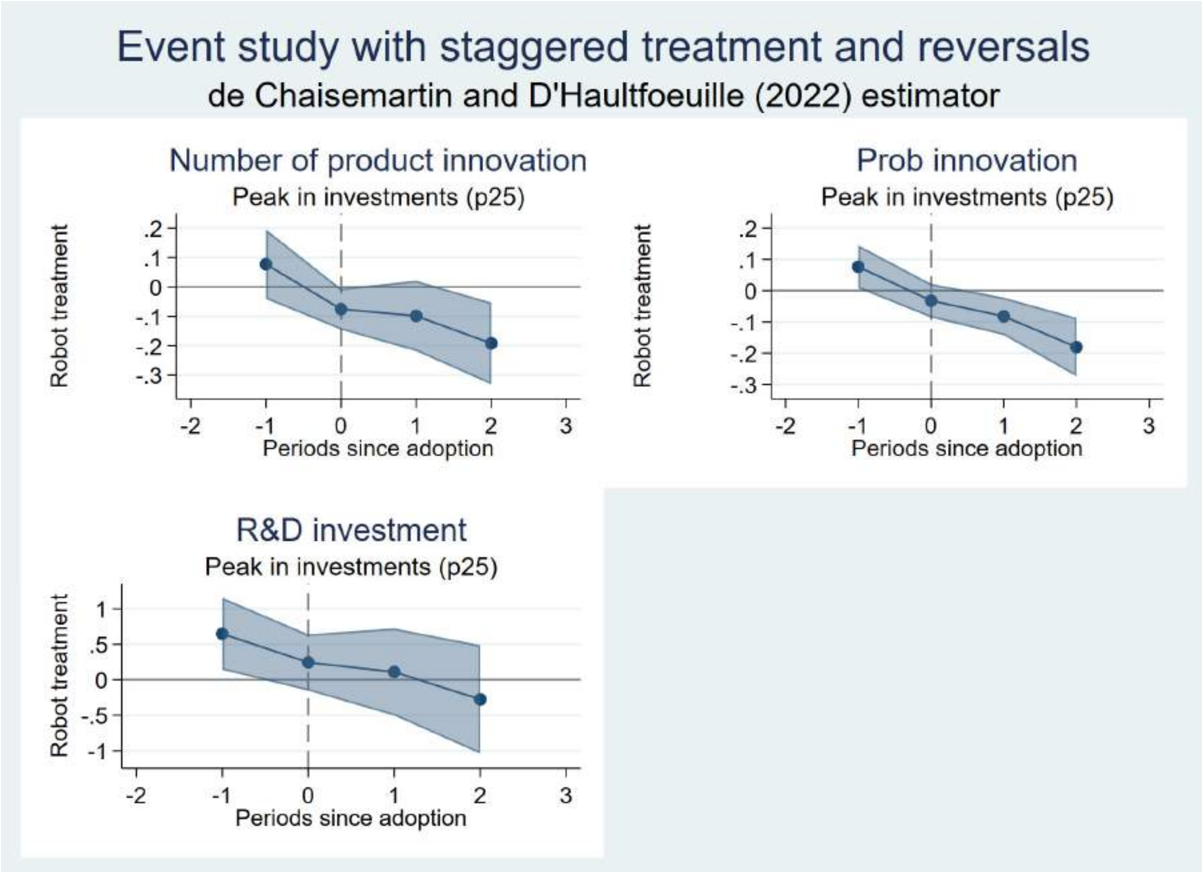
Notes: Standard errors are clustered at the firm level. Estimation is by de Chaisemartin and D'Haultfoeuille (2022) estimator, which is unbiased under treatment heterogeneity and the presence of reversals (groups switching in and out of treatment). The dependent variable are: i) the number of new (or significantly improved) products introduced during the relevant four-year period (upper-left panel); ii) a dummy variable taking value one when the firm introduced new (or significantly improved) products at least once during the relevant four-year period, and 0 otherwise (upper-left panel) and iii) the amount invested in R&D (bottom-left panel). All regressions include controls for R&D expenditure, firm size and investment in industrial equipment. The share of foreign ownership and export intensity are not included as controls due to lack of convergence in the computation of bootstrapped standard errors.

Figure A2. Robotisation and different types of product innovation: de Chaistemartin and D'Haultfoeuille (2022) estimator



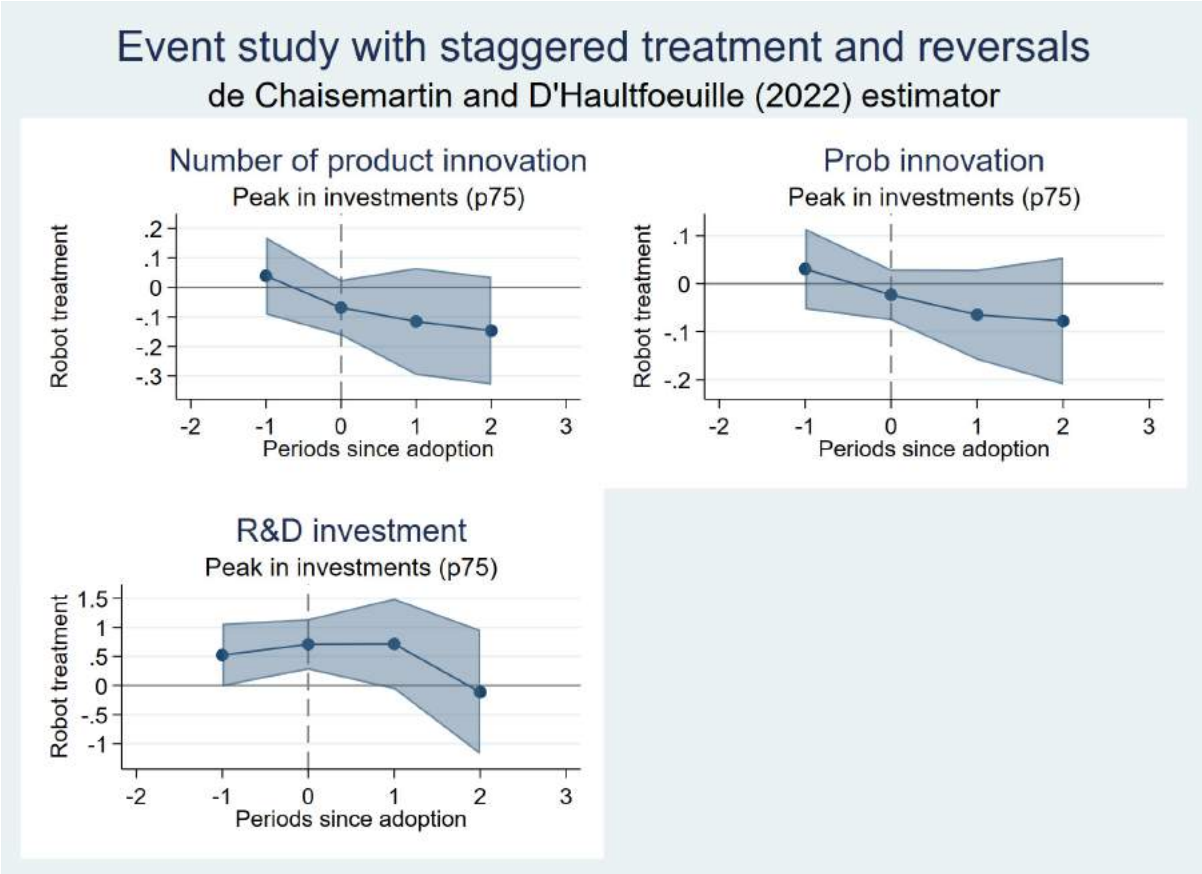
Notes: Standard errors are clustered at the firm level. Estimation is by de Chaisemartin and D'Haultfoeuille (2022) estimator, which is unbiased under treatment heterogeneity and the presence of reversals (groups switching in and out of treatment). The dependent variable are whether the firm introduced products with new (or significantly improved) materials (upper-left panel), components (upper-right panel) or functions (bottom-left panel) during the relevant four-year period. All regressions include controls for R&D expenditure, firm size and investment in industrial equipment. The share of foreign ownership and export intensity are not included as controls due to lack of convergence in the computation of bootstrapped standard errors.

Figure A3. Robotisation, R&D and product innovation: de Chaistemartin and D'Haultfoeuille (2022) estimator for small-scale investment (bottom quartile)



Notes: Standard errors are clustered at the firm level. Estimation is by de Chaisemartin and D'Haultfoeuille (2022) estimator, which is unbiased under treatment heterogeneity and the presence of reversals (groups switching in and out of treatment). The dependent variables are: i) the number of new (or significantly improved) products introduced during the relevant four-year period (upper-left panel); ii) a dummy variable taking value one when the firm introduced new (or significantly improved) products at least once during the relevant four-year period, and 0 otherwise (upper-left panel) and iii) the amount invested in R&D (bottom-left panel). All regressions include controls for R&D expenditure, firm size and investment in industrial equipment, except for R&D investment where we control only for firm size (due to lack of convergence in the computation of bootstrapped standard errors). The main explanatory variable refers to small-scale robotisation: when the adoption of robots coincides with an investment in industrial equipment within the first quartile.

Figure A4. Robotisation, R&D and product innovation: de Chaistemartin and D'Haultfoeuille (2022) estimator for large-scale investment (top quartile)



Notes: Standard errors are clustered at the firm level. Estimation is by de Chaisemartin and D'Haultfoeuille (2022) estimator, which is unbiased under treatment heterogeneity and the presence of reversals (groups switching in and out of treatment). The dependent variables are: i) the number of new (or significantly improved) products introduced during the relevant four-year period (upper-left panel); ii) a dummy variable taking value one when the firm introduced new (or significantly improved) products at least once during the relevant four-year period, and 0 otherwise (upper-left panel) and iii) the amount invested in R&D (bottom-left panel). All regressions include controls for R&D expenditure, firm size and investment in industrial equipment, except for R&D investment where we control only for firm size (due to lack of convergence in the computation of bootstrapped standard errors). The main explanatory variable refers to large-scale robotisation: when the adoption of robots coincides with an investment in industrial equipment above the upper quartile.

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